# **Supplementary Information**

**Article**: Nutritional status and the influence of TV consumption on female body size ideals in populations recently exposed to the media

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### <span id="page-1-0"></span>**Supplementary Methods.** Food insecurity questionnaire

- 1. How many meals do you have in a typical day? (*three or more, two or less*)
- 2. Do you have enough food to eat in a typical day? (*yes, no*)
- 3. Do all members of your household have enough food to eat in a typical day? (*yes, no*)
- 4. Where does most of the food you consume come from? (*mainly from shops, mainly from fishing or farming*)
- 5. Are there periods in the year when you diet changes significantly? (*yes, no*)
	- If so, specify period and diet (open-ended)
- 6. Are there periods in the year when it is more difficult to find food (e.g., crops or fish) or during which you are hungrier? (*yes, no*)
	- $-$  If so, specify period (open-ended)
- 7. Can you choose what you want to eat every day? (*yes, no*)
- 8. Do you sometimes wish you could eat something different or do you sometimes miss some foods (e.g., meat)? (*yes, no*)
- 9. In comparison with the surrounding communities, do you consider that your community has easier access or more difficult access to food and varied foods? (easier, more difficult)

*Note*. Answers to items 1-9 were coded as 0 and 1 and were summed for each participant, with a high score indicating a high food insecurity. Items 5, 6, and 8 were reversed when coding the data. Open-ended answers are not discussed in the current study.

<span id="page-2-0"></span>**Supplementary Table S1.** Two-step cluster analysis of nutrition data



*Note*. Some items were grouped for analysis. For example, coffee/tea with sugar, soft drinks, and sugared squash were grouped as 'sugared beverages'.

<span id="page-3-0"></span>**Supplementary Note.** Bayesian analysis**:** Stan Model code

#### data {

 int<lower=0> N1; // number of data items int<lower=0> N2; // number of data items int<lower=0> N3; // number of data items int<lower=0> K; // number of predictors

```
 matrix[N1, K] x1; // predictor matrix
 vector[N1] y1; // outcome vector
 matrix[N2, K] x2; // predictor matrix
 vector[N2] y2; // outcome vector
 matrix[N3, K] x3; // predictor matrix
 vector[N3] y3; // outcome vector
```
}

#### parameters {





real<lower=0> sigma; //error scale

vector[K] betamu; //beta prior real<lower=0> betasigma; //beta prior

 //real betamu2; //beta prior //real<lower=0> betasigma2; //beta prior

 //real betamu3; //beta prior //real<lower=0> betasigma3; //beta prior

```
 //real betahmu; //beta hyper prior
   //real<lower=0> betahsigma; //beta hyper prior
}
```

```
model {
```

```
y1 ~ normal(x1 * beta1 + beta01, sigma); // likelihood
//beta1 ~ ~ ~ normal(betamu1, betasigma1); // specify prior?
y2 \sim normal(x2 * beta2 + beta02, sigma); // likelihood
//beta2 \sim normal(betamu2,betasingma2); // specify prior?
y3 \sim normal(x3 * beta3 + beta03, sigma); // likelihood
//beta3 ~ ~ nonmal(betamu3,betasigma3); // specify prior?
```

```
 for (k in 1:K){
```
 beta1[k]~normal(betamu[k],betasigma); beta2[k]~normal(betamu[k],betasigma); beta3[k]~normal(betamu[k],betasigma);}



betamu  $\sim$  normal(0,10); betasigma  $\sim$  gamma(2,1);//7,1);

```
 //betamu2 ~ normal(betahmu,10);
//betasigma2 ~ gamma(betahsigma,1);
```
 $// between 3 ~-$  normal(betahmu, 10);  $//betasigma3 ~ & qamma(betahsigma,1);$ 

```
//betahmu \sim normal(0,10);
//betahsigma ~ gamma(7,1);
```

```
}
generated quantities {
```
real ll1 ; vector[N1+N2+N3] II3 ;

```
ll1<-normal_log(y1 , x1 * beta1 + beta01, sigma)+normal_log(y2 , x2 * beta2 + beta02, 
sigma)+normal_log(y3 , x3 * beta3 + beta03, sigma);
```

```
for (n in 1:N1)
   ll3[n]<-normal_log(y1[n] , x1[n] * beta1 + beta01, sigma);
for (n in 1:N2)
   ll3[n+N1]<-normal_log(y2[n] , x2[n] * beta2 + beta02, sigma);
for (n in 1:N3)
   ll3[n+N1+N2]<-normal_log(y3[n] , x3[n] * beta3 + beta03, sigma);
}
```
#### <span id="page-6-0"></span>**Supplementary Analysis. Frequentist Analyses**

Hierarchical regression models were used to identify predictors of peak BMI preference. Out of the fourteen independent variables, eight were found to significantly correlate with peak BMI preference and were therefore considered as potential predictors (full correlation matrix is shown in Supplementary Table S2; the variables BMI and WHR were standardised as they had been found to differ between sex). They were television consumption, three measures of nutritional status (diet quality score, food insecurity score, and size of last meal), as well as four control variables (earnings, economic score, education, and sex). Since no interaction was found between sex and location for peak BMI preference (see Results section), men and women were analysed together. All model coefficients are shown in Supplementary Table S3.

There were no multicollinearity issues as none of the predictors used in regression analyses had intercorrelations higher than 0.5, and tolerance values were higher than 0.6 across all analyses. Further, across all analyses, there were no studentized deleted residuals higher than ±3 standard deviations, and although a few leverage values were higher than 0.2 (up to 0.38 for one observation), there were no values for Cook's distance above 1 across all analyses (the observation with a 0.38 leverage had a corresponding Cook's value of 0.15, showing that it had a relatively low influence, and was therefore not discarded from analyses). Finally, across all analyses the residuals were approximately normally distributed as assessed by Q-Q plots.

To start with, all participants were analysed together and the four control variables were entered in a first model. Either nutritional status (second model) or television (third model) were then added to this initial model. When nutritional status was added, the initial model did not improve ( $R^2$  change = 0.034,  $F_{3, 90}$  = 1.42,  $p = .241$ ) and none of the nutritional measures predicted peak BMI preference. In contrast, when television consumption was added, the initial model improved ( $R^2$  change = 0.068,  $F_{1, 92}$  = 9.18,  $p = .003$ ,  $f^2 = 0.272$ ), and the only significant predictors were sex and television consumption, such that a lower peak BMI preference was associated with male gender and more TV consumption.

Comparisons between locations (see previous section) had shown that Village B and Village C differed on peak BMI preference and on television consumption, but not on nutritional status, suggesting that television consumption is the main determinant of female body size preferences. In contrast, Village A and Village B differed on peak BMI preference and on nutritional status, but not on television consumption, suggesting that nutritional status better accounts for female body size preference.

To clarify these results, separate regressions were run for Village B and Village C data together, and then for Village A and Village B data together. (We did not run

regressions for Village A and Village C data together because these communities differed on both television consumption and nutritional status). Using the same variables and the same regression method as above, adding nutritional status did not improve the initial models (Village B and Village C:  $R^2$  change = 0.028,  $F_{3.57}$  = 0.77,  $p > .250$ ; Village A and Village B:  $R^2$  change = 0.025,  $F_{3.62}$  = 0.67,  $p > .250$ ), whereas adding television consumption resulted in a significant improvement (Village B and Village C:  $R^2$  change = 0.053,  $F_{1,59}$  = 4.70,  $p =$ .034,  $f^2 = 0.188$ ; Village A and Village B:  $R^2$  change = 0.055,  $F_{1, 64} = 4.72$ ,  $p = .033$ ,  $f^2 =$ 0.280), leaving again sex and television consumption as the only significant predictors of peak BMI preference in the final models.

Regressions were finally used to rule out the possibility that the differences in peak BMI preference between the above locations could be due to other unmeasured variables. To do so, all variables used above were entered together in a first model, to which location was added hierarchically. Location did not improve the first model for either Village B and Village C ( $R^2$  change = 0.004,  $F_{1,55}$  = 0.35,  $p > .250$ ) or Village A and Village B (increase in  $R^2$  change = 0.013,  $F_{1.60}$  = 1.055, *p* > .250.

# **Supplementary Table S2.** Full correlation matrix (N for all analyses = 110;  $^*p$  < .05,  $^{**}p$  < .01)

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## <span id="page-9-0"></span>**Supplementary Table S3.** Hierarchical regression analyses of predictors of peak BMI preference





1.  $R^2$  = .250,  $F[4, 93]$  = 7.758,  $p < .0001$ ; 2.  $R^2$  = .284,  $F[7, 90]$  = 5.103,  $p < .0001$ ; 3.  $R^2$  = .318,  $F[5, 92]$ = 8.590, *p* < .0001; 4. *R<sup>2</sup>* = .281, *F*[4, 60] = 5.874, *p* < .0001; 5. *R<sup>2</sup>* = .309, *F*[7, 57] = 3.649, *p* < .005; 6. *R<sup>2</sup>* = .334, *F*[5, 59] = 5.929, *p* < .0001; 7. *R<sup>2</sup>* = .196, *F*[4, 65] = 3.962, *p* < .01; 8. *R<sup>2</sup>* = .221, *F*[7, 62] = 2.518, *p* < .05; 9. *R<sup>2</sup>* = .251, *F*[5, 64] = 4.296, *p* < .005.